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ORIGINAL ARTICLE

Reconfiguration schemes evaluation based on preference ranking of key characteristics of reconfigurable manufacturing systems

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Abstract To address the problem of how to build quantitative evaluation index models that reflect the essential characteristics of reconfigurable manufacturing system (RMS) and rank alternative reconfiguration schemes, which possess both advantages and disadvantages, an evaluation method based on the preference ranking organization method for enrichment evaluation (PROMETHEE) is proposed. Based on a consideration of the reconfiguration of the reconfigurable machine components and manufacturing cells, quantitative models of the key characteristics of an RMS (scalability, convertibility, diagnosability, modularity, integrability, and customization) are established, after which the quantitative models are used as the basis for constructing an RMS evaluation index system. The analytic hierarchy process (AHP) is used to assign the weights for these indices. During the evaluation process, PROMETHEE I is first applied to analyze the advantages and disadvantages of each alternative scheme. Then, PROMETHEE II is adopted to analyze the net advantages of the schemes. Finally, all of the alternative configurations are ranked according to the analysis results above. The workshop of an institute that has both research and production capabilities was used as an example to validate the effectiveness and practicability of the proposed method. The example contains 10 alternative reconfiguration schemes, and each scheme consists of six evaluation indices. The computation result shows that quantitative models of six key RMS characteristics are equipped with the ability of quantitative description of the RMS reconfiguration scheme, which gives intuitive decision-making information combined with PROMETHEE, including advantage and disadvantage between alternative schemes, for a decision-maker to select the satisfactory configuration. In addition, only a 7.2 % data loss during the evaluation data processing means the rationality of the selected evaluation index and evaluation algorithm.

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1 Introduction

Nowadays, the global economy is complicated and unpredictable. The manufacturing industry is under tremendous pressure from the buyers' market, ranging from fluctuations in product demand to product diversity. Customized production has become the trend. In order to stay competitive, manufacturing companies must remain highly sensitive to the market (fluctuations) and be able to react quickly to market changes by introducing products that meet customer needs in a timely manner. As a new type of leading manufacturing systems, reconfigurable manufacturing systems (RMSs) have attracted a great amount of attention from companies [1].

Koren et al. [2] was the first to describe how the configuration has a vital impact on the performance of the RMS and pointed out that parallel configurations with cross-over yield significant benefits in throughput, scalability, and performance when identical machines are used throughout the system. An RMS is a manufacturing system created at the design stage to be capable of making rapid changes in the structure and hardware/software components to quickly adjust the production capacity and functionality in response to sudden changes in irregular market demand [3, 4]. An RMS is designed around a part family and provides customized flexibility to manufacture all the members of the part family [1]. In a real shop floor scenario, the manufacturers have to deal with varied number of orders for multiple part families, and after producing the orders of a particular family, they need to switch over to the orders of a different part family [5]. Changing over from one part family to another may require the system's reconfiguration, which is a complex process and involves changing from one configuration to another depending on the existing initial configuration and the new configuration required for subsequent production of orders. Therefore, to achieve the sustainable reconfiguration and rapid responsiveness of the system during the entire life cycle, the effective evaluation and selection of RMS configurations are critical. The evaluation of an RMS is a multi-criteria decision (MCD)-making problem, and scholars around the world have conducted extensive and in-depth research on this subject. To measure the performance of RMS, the key characteristics such as scalability, convertibility, diagnosability, modularity, integrability, and customization should be considered [6].The existing studies have mainly focused on general evaluation indices for manufacturing systems, such as the production time and cost, but lack quantitative indices that can reflect key RMS characteristics. In addition, the ranking of alternative reconfiguration schemes is mainly based on the advantages and disadvantages of the alternatives, i.e., reconfiguration schemes with greater advantages and fewer disadvantages would be more highly ranked. However, in cases where reconfiguration schemes have both significant advantages and disadvantages, ranking and decision making are difficult and cannot be solved using the currently available methods. To address this issue, an evaluation index system for RMS reconfiguration schemes was established in this study, which was initiated based on six key RMS characteristics. Moreover, mathematical models for the indices were established to realize quantitative evaluation. The analytic hierarchy process (AHP) methodology is used to weigh the indices. An approach based on the preference ranking organization method for enrichment evaluation (PROMETHEE) was used to make compressive and objective evaluations of alternative reconfiguration schemes. Specifically, PROMETHEE I and PROMETHEE II were applied to make partial and complete evaluations, respectively. Furthermore, the validity and practicality of the evaluation results were examined using geometric analysis for interactive aid (GAIA).

The literature review on the subject is summarized in the next section. In Sect. 3, quantitative models for the six key RMS characteristics are analyzed and developed. In Sect. 4, a detailed description is provided for the calculation methods proposed in this work, including the determination of index weights using the AHP method, as well as the calculation procedures for the PROMETHEE methods. In Sect. 5, a verification test is conducted, which proves the validity of the calculation methods through a case study. In the last section, conclusions are drawn from the research conducted in this study.

2 Literature review

As early as the year 1999, the concept of RMS was proposed under the joint efforts of Professor Koren and many other well-known scholars [1]. They stated that the system enjoyed the advantages of both low cost and high efficiency. They also stressed that an RMS must be designed at the outset to be reconfigurable; otherwise, the reconfiguration process will be lengthy. In addition, Professor Koren listed the six key characteristics that an RMS must possess [1, 3, 4], including modularity, integrability, customization, convertibility, diagnosability, and scalability. Only when a manufacturing system possesses these six key characteristics can it achieve the manufacturing goals of low cost, high quality, and rapid responsiveness. An evaluation of an RMS is needed to determine whether it possesses these characteristics and to evaluate the system performance.

Based on an analysis of the factors influencing RMS performance, Wu et al. [7] established a hierarchical and comprehensive evaluation index system. They also used the grey relational analysis method to calculate index weights and carried out fuzzy comprehensive evaluations of reconfiguration schemes. Based on comprehensive assessments of qualitative and quantitative factors, Dou et al. [8] established a hierarchical configuration-evaluation model that took into account the productivity, product quality, convertibility, scalability, and cost. They also proposed a hybrid analytical hierarchy decision-making method that improved the decision-making efficiency for RMS reconfiguration schemes. Rehman et al. [9] proposed an AHP RMS-evaluation framework, assessing RMS configuration schemes at three levels (system, unit, and machine) using productivity as the evaluation index, in order to determine the optimal scheme. Based on the analysis of the machine reconfigurability and operational capability of a reconfigurable machine tool, Goyal et al. [10] evaluated reconfiguration schemes using a two-phase method, while cost was used as the optimization goal. They also stressed the necessity of reconfigurability analysis during the evaluation and selection processes. Saxena et al. [11] proposed a three-phase evaluation approach for RMS reconfiguration schemes: at phase one, a needs analysis was conducted; at phase two, RMS reconfiguration alternatives were designed; and at phase three, an evaluation of the reconfiguration alternatives was conducted using indices that included the reconfiguration cost, maintenance cost, and machine utilization. The optimal or near-optimal reconfiguration design was selected by mathematical computation using an artificial immune system. To address the insufficiency of RMS evaluation systems, Yuan et al. [12] considered the practical engineering applications and established an AHP-based RMS evaluation system to evaluate the system from the perspectives of economy, production performance, reconfigurability, environment, and the risk of an RMS. Moreover, the meaning and significance of each index were analyzed. This study provided a good idea for an RMS evaluation system by combining the AHP and fuzzy synthetic evaluation. However, the settings of the indices for the evaluation were too broad, while key RMS characteristics were not evaluated, which might cause large errors in the evaluation results. Guan et al. [13] also employed a fuzzy comprehensive evaluation method. Despite the unspecified indices used in the study, it proposed the use of PowerBuilder (PB) software, which achieved good outcomes in the practical application of RMS evaluation. As shown in Table 1, the advantages and disadvantages of existing methods on RMS evaluation are summarized.

The evaluation of an RMS is an MCD-making process, which can be addressed by methods that include the AHP, fuzzy comprehensive evaluation, and the methods within the family of outranking methods (such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE)). Abdi et al. [14] used the AHP to build a decision-making system for RMS configurations. In addition, based on an analysis of the production cost and quality, a new evaluation index, called manufacturing responsiveness, was proposed for evaluating alternative schemes. Later, based on the earlier research results, Abdi conducted further research on the use of fuzzy AHP (FAHP) for the evaluation and selection of RMS configurations [15]. The introduction of fuzzy multi-criteria models that integrate multiple indices involving the economic mode, quality, production capacity, etc., ensured that the selection results were more applicable in actual practice. Singh et al. [16] established an MCD-making module using the AHP, which was combined with fuzzy logic to conduct pairwise comparisons of alternatives. The authors also tried to quantify qualitative indices, which improved the efficiency and accuracy of the selection results. Moreover, the use of intelligent algorithms has

Table 1 Summarization of existing methods on RMS evaluation

	Advantage	Disadvantage
Wu et al. [7]	A hierarchy synthetical evaluation index system was proposed, and grey relational analysis method was used to calculate the weight of indices.	This method did not give quantitative model of evaluation index.
Dou et al. [8]	A hierarchical configuration-evaluation model was developed considering qualitative and quantitative performance criteria.	Evaluation index system contains qualitative index.
Goyal et al. [10]	Pointed out the necessity of reconfiguring ability in configuration evaluation	Two-stage evaluation method is too cumbersome and inefficient.
Rehman et al. [9]	Evaluated the RMS scheme from three levels, the manufacturing system, manufacturing cell, and machine tool, facilitates the practical application	Configuration was evaluated under different conditions, which reduces the flexibility of the algorithm due to the difficulty of making complete enumeration of the condition.
Saxena et al. [11]	Order demand, alternative configurations, and evaluation index are analyzed in detail	The artificial immune system algorithm used in the process of scheme selection has defects itself and need to be improved before use.
Guan et al. [13]	Developed an RMS configuration evaluation software, which improves the efficiency of configuration evaluation	Just put forward the evaluation index selection rules and no evaluation index was proposed
Yuan et al. [12]	A systematic and comprehensive evaluation model for RMS was proposed based on the hierarchy analysis, and the meaning of each index was analyzed.	Evaluation index system is too big, which leads to redundant information and reduces evaluation accuracy. In addition, some index is hard to be quantified.

achieved good results in addressing this issue [10, 17, 18]. Monitto et al. [19] used a FAHP method to evaluate automated manufacturing systems. The FAHP method was able to address uncertainty and to take into account both the output and flexibility issues. The study by Monitto et al. [19] aimed to provide a complete, accurate, and value-driven decision support system that could support the selection of the optimal automated manufacturing system.

However, the applications of the AHP and fuzzy comprehensive evaluation in multi-criteria analysis are very complicated, and the computation procedures of intelligent algorithms and some outranking methods (such as TOPSIS) themselves are very complex, introducing a certain degree of difficulty in practical applications. The PROMETHEE approach within the family of outranking methods is able to overcome these difficulties and has attracted much attention because it is simple and easy to use [20]. The PROMETHEE approach includes PROMETHEE I and PROMETHEE II: PROMETHEE I provides partial ranking and PROMETHEE II provides a complete ranking of the alternatives. Some conclusions derived from PROMETHEE I might contradict each other, while some detailed data might be lost when using PROMETHEE II, leading to wrong decisions eventually being made. Therefore, the complementary use of PROMETHEE I and PROMETHEE II can ensure accurate outcomes. Macharis et al. [21] analyzed the advantages and disadvantages of the PROMETHEE method and recommended using the strengths of the AHP method to increase the suitability of PROMETHEE. Dagdeviren et al. [22] proposed an integrated AHP-PROMETHEE approach for multi-criteria equipment selection. In this approach, AHP was used to determine the evaluation criteria system and weights of the indices, and then the PROMETHEE method was used to rank the alternatives based on the AHP results. Moreover, the GAIA method was used for a sensitivity analysis of the weights. Behzadian et al. [23] presented a comprehensive review of the PROMETHEE methodologies. Based on a review of 217 research papers from 100 journals, the authors gave a detailed description of the current research on PROMETHEE methodologies, as well as their combined applications with other methods. In addition, numerous researchers have attempted to combine the AHP, fuzzy comprehensive evaluation, and outranking methods to improve the evaluation performance. In order to solve complex multi-criteria multi-alternative problems, Mousavi et al. [17] proposed an integrated Delphi–AHP–PROMETHEE approach. First, the Delphi method was used to determine the evaluation criteria system. Then, AHP was applied to analyze the weights of the criteria. Finally, the PROMETHEE method was employed to rank the alternatives, and the decision makers could make decisions based on the ranking results. Roodposhti et al. [24] combined the use of PROMETHEE II with FAHP during the MCD-making process, which improved the weighting accuracy and credibility of the evaluation results.

3 Quantitative models of evaluation indices based on key RMS characteristics

The six key RMS characteristics, i.e., scalability, convertibility, diagnosability, modularity, integrability, and customization, essentially reflect the production capacity, reconfigurability, and responsiveness of an RMS. Therefore, an RMS evaluation index system that is developed based on these key characteristics can comprehensively reflect the RMS capacity and performance. However, these six key characteristics are qualitative descriptions of an RMS, and an evaluation of RMS reconfiguration schemes using qualitative indices is unlikely to obtain objective and fair evaluation results. Therefore, it is necessary to deeply analyze the meaning of each index and identify the RMS internal factors related to each of them. Subsequently, based on the index analysis results, a mathematical model is established for each index, realizing the conversion of a qualitative evaluation to a quantitative evaluation.

3.1 Quantitative model of RMS scalability

RMS scalability (S) refers to the capability of an RMS to adjust the system production capacity by adding/removing machine tool modules or machine tools and rearranging processing steps in response to a change in production batches [25].

Scalability is measured by the amount of adjustment needed in response to fluctuations in the market demand. If the current RMS is able to satisfy the market demand by only making small adjustments, this RMS is considered to have high scalability; otherwise, if an RMS has lower or even zero scalability, it is considered that this RMS does not have the needed scalability. In actual production, adjustments of the system production capacity are determined based on the production batch size and smoothness of the adjustments [26]. Therefore, the concept of gradient adjustment is introduced in this paper. This concept indicates that the amount of RMS scaling is not random, and instead, production capacity should be adjusted according to an adjustment gradient based on the actual condition of the RMS. In addition, the RMS is able to generate many configurations during the entire life cycle by reconfiguring the system, with each configuration having a certain production capacity. Therefore, the maximum and minimum production capacity values among all the configurations can be objectively identified. After identifying the adjustment gradient, maximum production capacity, and minimum production capacity, following a reconfiguration order of an RMS from the one with the minimum production capacity to the one with the maximum production capacity, the number of reconfigurations is calculated according to the adjustment gradient. In addition, the parameters for each reconfiguration, including the cost, time, adjustment amount at the system level, and adjustment amount at the machine level, are calculated. Reconfiguration time and cost are the key factors in the process of RMS production capacity scaling. Too much time and cost will reduce the RMS reconfiguration performance. The adjustment amount of system level and machine level directly reflects the workload of capacity scaling, and the purpose of reconfiguration is in pursuit of the lowest workload. Finally, based on these parameters, a quantitative model using Eqs. (1), (2), (3), and (4) is established for the RMS scalability evaluation.

$$S = 1 - \frac{1}{\Delta_{\max} - \Delta_{\min}} \times \frac{1}{N_\Delta} \sum_{i=1}^{N_\Delta} \lambda_i{}^T \lambda_i{}^C \alpha_i \Delta_i \tag{1}$$

$$\lambda_i^T = \frac{T_i}{T_i^p} \tag{2}$$

$$\lambda_i{}^C = \frac{C_i}{C_i^p} \tag{3}$$

$$\alpha_i = \frac{\omega_1 N_i^a + \omega_2 N_i^m}{N_i} \tag{4}$$

where S refers to the RMS scalability, which is a dimensionless value that falls within the range of 0–1, with a near-1 value indicating a higher RMS scalability and a near-0 value indicating a lower scalability or even no scalability. $\Delta_{\max}$ and $\Delta_{\min}$ denote the maximum and minimum RMS production capacities, respectively. For example, if a given RMS contains six machine tools and can generate eight different configurations through reconfiguration, with each configuration corresponding to one production capacity, this RMS has a total of eight production capacities. The maximum and minimum values among these eight production capacities are the maximum production capacity $\Delta_{\max}$ and the minimum production capacity $\Delta_{\min}$ defined in this paper, respectively. Δ_i is the adjustment gradient. The reconfiguration of an RMS from the minimum production capacity $\Delta_{\min}$ to its maximum state $\Delta_{\max}$ requires multiple adjustments according to the adjustment gradient. This means that during the reconfiguration of an RMS, the production capacity changes based on the adjustment gradient. The adjustment gradient can be a constant or a variable. N_Δ is the number of adjustment gradient steps that exist between the minimum and maximum RMS production capacities, i.e., the number of reconfigurations required to adjust the production capacity from its minimum to maximum value. $\lambda_i{}^T$ is the time parameter required to complete the adjustment gradient Δ_i. T_i denotes the reconfiguration time required to complete the adjustment gradient Δ_i. T_i^p refers to the production cycle for the i$^{\text{th}}$ reconfiguration. $\lambda_i{}^C$ refers to the cost parameter required to complete the adjustment gradient Δ_i. C_i means the reconfiguration cost required to complete the adjustment gradient Δ_i. C_i^p is the production cost for the i$^{\text{th}}$ production cycle. α_i denotes the adjustment parameter (the system level and machine tool level) required to complete the adjustment gradient Δ_i. The system-level parameter corresponds to the adjustments that change the system configuration, such as adding, removing, and moving machine tools. The machine-tool-level parameter corresponds to reconfiguration adjustments of machine tools such as changes in spindles and tools. $N_i{}^a$ denotes an adjustment parameter at the system level because it is assumed that the reconfiguration is a minimum-to-maximum adjustment in RMS production capacity; only the addition of machine tools is considered. $N_i{}^m$ denotes an adjustment parameter at the machine tool level, i.e., the number of machine tools that require the addition of spindles and tool changes. ω_1 and ω_2 mean the weights of the system-level adjustment parameter and the machine tool-level adjustment parameter, respectively, and $\omega_1 + \omega_2 = 1$,which can be calculated by AHP algorithm. N_i denotes the number of machine tools in an RMS before the adjustment gradient Δ_i is completed.

3.2 Quantitative model for RMS convertibility

Convertibility (C_y) is defined as the capability of an RMS to rapidly adjust the production functionality in response to market demand [27], including the conversion of its production functionality to produce different part families and different parts within the same part family. RMS functionality conversions usually involve the replacement of machine tools and changes in machine tool settings, which change the original RMS production functionality.

According to the definition of convertibility, a convertibility model is developed in this paper based on the conversions between part families and between different parts in the same part family. Koren et al. [1] pointed out that an RMS must possess the capacity to process all of the parts within a part family. Functionality conversion does not involve issues such as the addition, removal, or replacement of machine tools, but only requires adjustments at the machine tool level such as the adjustment of the machine spindle, replacement of cutting elements, and changes in fixtures. Therefore, an analysis of the functionality conversion between parts only considers adjustments at the machine tool level. However, during the analysis of functionality conversion between part families, adjustments at both the machine tool level and system level should be considered, with the latter including the addition, removal, replacement, and movement of machine tools. Based on the above analysis, a quantitative RMS convertibility model using Eqs. (5), (6), and (7) is established.

$$C_v = \omega_1 C_1 + \omega_2 C_2 \tag{5}$$

$$C_1 = \frac{1}{\frac{1}{2N_p - 1}\sum_{i=1}^{N_p-1}\sum_{j=i+1}^{N_p}\left(N_{ij}^s + N_{ij}^t + N_{ij}^f\right)} \tag{6}$$

$$C_2 = \frac{1}{S_c \times (N_a + N_d + N_r + N_m)} \tag{7}$$

where C_v is the RMS convertibility and ranges from 0 to 1, with a value closer to 1 indicating a stronger RMS convertibility and, conversely, a weaker convertibility. C_1 and C_2 mean the RMS convertibility within a part family and between part families, respectively. ω_1 and ω_2 mean the weights of C_1 and C_2, respectively, and the weight value can be calculated by AHP algorithm. N_p denotes the types of parts in the part family (RMS capability to produce all parts of the part family). $2N_p - 1$ denotes the total number of conversions between parts within the part family. N_{ij}^s, N_{ij}, and ${}^tN_{ij}^f$ respectively denote the number of machine tools that need spindle adjustment, the number of machine tools that need cutting tool adjustment, and the number of machine tools that need fixture adjustment when the production of the i^{th} part is converted to the production of the j^{th} part. S_c is a similarity coefficient between the part families in the conversion. N_a, N_d, N_r, and N_m respectively denote the numbers of machine tools that need to be added, removed, replaced (including the replacement of machine tools, spindles, cutting tools, and fixtures), or moved during the conversion between part families.

3.3 Quantitative model for RMS diagnosability

RMS diagnosability (D) is defined as the ability to make a diagnosis rapidly in order to reduce the ramp-up time after reconfiguration [28], i.e., the ability of an RMS to detect the ultimate cause of product quality defects and make adjustments to achieve the objective of reducing ramp-up time. The length of the ramp-up time depends on the RMS diagnosability, and an excessively long ramp-up time would lower the RMS responsiveness, influencing the implementation of reconfiguration schemes. RMS diagnosability is associated with the number of diagnosis steps, sample size for diagnosis, and diagnostic accuracy. Quality diagnostics is a complex process, and more diagnostic procedures mean increasing production time, which will drop the efficiency of production. Similarly, a too big diagnosis sample size leads to increase of diagnostic time. Moreover, diagnostic accuracy directly reflects RMS diagnosability. Based on the above analysis, a quantitative model for RMS diagnosability evaluation is established, as shown in Eqs. (8), (9), (10), and (11).

$$D = \frac{1}{N_D}\sum_{i=1}^{N_D} \lambda_i^d \lambda_i^s \lambda_i^T X_i \tag{8}$$

$$\lambda_i^d = \frac{N_i^{d0}}{N_i^d} \tag{9}$$

$$\lambda_i^s = \frac{N_i^{s0}}{N_i^s} \tag{10}$$

$$\lambda_i^T = \frac{T_i^p}{T_i^r} \tag{11}$$

where D denotes the RMS diagnosability ($D > 0$), with a larger D value indicating a better RMS diagnosability. N_D denotes the number of RMS reconfigurations. X_i is the accuracy of the quality testing on products during the RMS ramp-up period after the i^{th} reconfiguration, and the accuracy data from production data statistics can be obtained. N_i^{d0} denotes the total number of machine tools the RMS contains after the i^{th} reconfiguration. N_i^d means the number of pieces of diagnostic equipment in the manufacturing system after the i^{th} reconfiguration. λ_i^d denotes the diagnostic equipment factor. N_i^{s0} refers to the total number of products manufactured during the RMS diagnosis after the i^{th} reconfiguration. N_i^s refers to the size of the samples extracted during the RMS diagnosis after the i^{th} reconfiguration. λ_i^s denotes the sampling factor. T_i^p denotes the RMS production cycle after the i^{th} reconfiguration. T_i^r denotes the RMS ramp-up time after the i^{th} reconfiguration. λ_i^T means the ramp-up time factor.

3.4 Quantitative model for RMS modularity

RMS modularity (M) means that the design of a system is carried out using the modular concept. A module is an independent unit, which can be conveniently combined, reset, replaced, and exchanged with other units to construct different configurations or systems [13]. RMS modularity is generally used to describe the machine tools in the system, i.e., modular machine tools. A modular machine tool has the ability to alter the production capacity and production functionality by adjusting the machine tool modules in response to changes in market demands.

The number of modules in a modular machine tool is not positively correlated with the performance; a greater number of modules would lead to a higher cost for modulus management. Module granularity is a term used to decide whether the number of modules in a machine tool matches its functionality or production capacity. Values of module granularity follow a normal distribution, indicating the existence of an optimum number of modules that corresponds to the optimum module granularity. The maximum value of module granularity is 1. This means that if the number of modules is greater or fewer than the number that corresponds to this specific point, the granularity value would be less than 1 or even equals to 0. The independence of a module is associated with the efficiency of the RMS reconfiguration. On a machine tool level, the independence of a module is reflected by the number of interfaces for machine tool modules, with fewer interfaces and less coupling between modules associated with a higher module independence. On the system level, module independence is indeed the independence of a manufacturing unit, with a smaller amount of part cross-unit processing associated with a higher independence for the manufacturing unit. Based on the above analysis, a quantitative model is established for the RMS modularity evaluation, as shown in Eqs. (12), (13), and (14).

$$M = \omega_1 M_1 + \omega_2 M_2 \tag{12}$$

$$M_1 = \frac{1}{N_\Delta}\sum_{k=1}^{N_\Delta}\left(\frac{1}{\sum\limits_{i=1}^{P} N_i}\sum_{i=1}^{P} G_i \sum_{j=1}^{N_i}\frac{1}{N_{ij}}\right) \tag{13}$$

$$M_2 = \frac{1}{N_\Delta}\left(\frac{1}{\sum\limits_{k=1}^{N_\Delta} N_k}\sum_{k=1}^{N_\Delta} G_k \sum_{l=1}^{N_k}\frac{1}{N_{kl}}\right) \tag{14}$$

where M refers to the RMS modularity, which falls between 0 and 1. A value for M closer to 1 indicates a higher modularity. Otherwise, the modularity is lower. M_1 and M_2 refer to the modularity at the machine tool level and system level, respectively. M_1 analyzes the module granularity and module interfaces of the machine tool while M_2 analyzes the module granularity and module interfaces of the system. ω_1 and ω_2 mean the weightings of M_1 and M_2, respectively, which can be computed by AHP. N_Δ denotes the number of adjustment gradient steps between the minimum and maximum RMS production capacities, i.e., the number of RMS reconfigurations required from the minimum to maximum production capacity. P denotes the number of RMS processing steps, i.e., the number of machine tools (assuming that each step corresponds to one machine tool). N_i denotes the number of modules that the i^{th} machine tool contains. G_i denotes the module granularity of the i^{th} machine tool, which has a value between 0 and 1, with a value closer to 1 indicating a more reasonable module division. G_k denotes the module granularity of the k^{th} reconfiguration, which is similar in nature to G_i. Module granularity measures the rationality of the module number, which connects together through a certain mapping relationship. N_{ij} is the number of interfaces at the j^{th} module of the i^{th} machine tool. N_k is the number of units after the k^{th} reconfiguration, i.e., the number of system-level modules. N_{kl} denotes the number of repetitions of cross-unit processing for the l^{th} unit (system-level module) after the k^{th} reconfiguration (i.e., the number of interfaces at the system-level module).

3.5 Quantitative model for RMS integrability

RMS integrability (I) refers to the ability to integrate components (manufacturing machines and control modules) through the interfaces possessed by the components and the capability to integrate a new technique or process into the current system [4]. During reconfiguration, uniform interface standards for the software and hardware of the machine tool modules would largely reduce the correction (software/hardware interface adjustment and control program adjustment) time and cost, which can even be zero. If the interfaces are not standardized, interface amendment (standardization) is required, and this standardization process must be completed before the installation and setting can be performed to achieve the required functionality and production capacity. In the process of RMS integration, the software/hardware interface adjustment time and cost are in inverse relation to the integrability of RMS. Therefore, it is necessary to analyze the software/hardware interface adjustment time and cost. Based on this, a quantitative model for RMS integrability is established, as shown in Eqs. (15), (16), and (17).

$$I = \sum_{i=1}^{P}\sum_{j=1}^{N_i}\left(\omega_1\alpha_j^h + \omega_2\beta_j^s\right) \tag{15}$$

$$\alpha_j^h = 1 - \frac{1}{2}\left(\frac{C_j^{ha}}{C_j^h} + \frac{T_j^{ha}}{T_j^h}\right) \tag{16}$$

$$\beta_j^s = 1 - \frac{T_j^{sa}}{T_j^s} \tag{17}$$

where I denotes the RMS integrability, which has a range of 0–1, with a value closer to 1 indicating better integrability, and 1 further away showing worse integrability. P denotes the number of RMS machine tools. N_i denotes the number of modules contained in the i^{th} machine tool. $\alpha_j{}^h$ means the hardware adjustment parameter for the j^{th} module of the i^{th} machine tool. $\beta_j{}^s$ means the software adjustment parameter for the j^{th} module of the i^{th} machine tool. ω_1 and ω_2 denote the weightings of the hardware and software adjustment parameters, respectively, and $\omega_1+\omega_2=1$. $C_j{}^{ha}$, $C_j{}^h$, $T_j{}^{ha}$, $T_j{}^h$, $T_j{}^{sa}$, and $T_j{}^s$ denote the respective hardware setting cost, hardware installation cost, hardware setting time, hard installation time, interface setting time, and software setting time for the j^{th} module of the i^{th} machine tool. During system reconfiguration, smaller proportions of hardware adjustment cost/time and software adjustment time indicate a higher system integrability.

3.6 Quantitative model for RMS customization

RMS customization (C_m) refers to the selection of machine tools and component systems based on the flexibility needed for the processing of a part family and specific parts, i.e., to manufacture customized products with the customized functionality through reconfiguration [3]. Customization involves the part family and processing equipment, and two aspects need to be considered for RMS customization evaluation: the product and functionality. First, the RMS products undertaken need to be grouped into families. Next, RMS configurations are selected or designed according to the part family—the efficiency of this process is crucial to the customization performance. In terms of functionality, customization means a high utilization rate for the equipment. Higher equipment utilization indicates the stronger capability of the RMS to complete the processing of all types of parts of the part family and hence stronger customization capability. Based on the above analysis, a quantitative model is established for RMS customization, as shown in Eqs. (18), (19), and (20).

$$C_m = \lambda_T \times Y \times P \tag{18}$$

$$\lambda_T = 1\text{-}\frac{T_{pf}}{T_0} \tag{19}$$

$$Y = \frac{1}{P}\sum_{i=1}^{P}\frac{N_i}{N} \tag{20}$$

where C_m means the RMS customization, which is in the range of 0–1, with a value closer to 1 indicating a stronger RMS customization capability. λ_T refers to the impact factors for the part family construction time. T_{pf} denotes the time required from the construction of a part family to the completion of the configuration, with a longer time needed to construct the part family indicating a weaker RMS customization. T_0 denotes the production cycle. P is the types of parts of the family. Y means the RMS equipment utilization. N_i denotes the number of machine tools used for the i^{th} part. N denotes the total number of machine tools contained in the RMS. A shorter construction time for the part family and higher machine tool utilization during the production process will produce a stronger customization of the manufacturing system.

4 Integrated PROMETHEE–AHP approach for RMS reconfiguration evaluation

Decision makers often face a dilemma when evaluating reconfiguration schemes: some schemes have an absolute advantage in terms of specific indices but have poor performance on others. Decisions might be made based on the advantages, and other alternatives must be excluded based on the disadvantages or comprehensive evaluation results. It is difficult for decision makers to make effective decisions when confronted with numerous alternative schemes. To address this issue, the PROMETHEE method [20] is used in this paper to evaluate reconfiguration schemes. PROMETHEE is a multi-objective decision-making method based on pairwise comparisons of alternatives, which provides a set of ranking computational methods for decision makers. It includes PROMETHEE I for partial ranking and PROMETHEE II for complete ranking. Decision makers can select the preference function for each index according to their own preference combined with reality. Starting from the advantages and disadvantages of the schemes, the "advantageous flow" and "disadvantageous flow" of the candidate schemes are calculated, from which the partial or entire ranking of the scheme set is obtained. The PROMETHEE method has many advantages, but it is not able to assign weights to the indicators. Therefore, AHP is combined with the PROMETHEE method; AHP is used to determine the index weights first, followed by the use of the PROMETHEE method for decision making.

4.1 AHP-based index weight assignment for evaluation of reconfiguration schemes

In different RMS scenarios, each evaluation index has a different importance. Therefore, it is necessary to assign weights to the evaluation indices; however, this weight assignment is usually carried out based on the experience of the decision makers and thus has some uncertainty. In order to increase the scientific value of weight assignment, the AHP method is used to make pairwise comparisons between different indices according to an importance rating scale [8, 11, 13] (Table 2), which gives the weight vectors of the indices.

Table 2 Importance scale of evaluation index

Degree of importance	Definition and explanation
1	Two indices are equally important.
3	One index is slightly more important than the other.
5	One index is more important than the other.
7	One index is essentially more important than the other, which has been demonstrated.
9	One index is absolutely more important than the other.
2, 4, 6, 8	Intermediate importance between adjacent degrees described above
$1/a_{ij}$	The reciprocal of the importance scale

Furthermore, a consistency test was conducted.

Assuming that there are n evaluation indices, pairwise comparisons produce an $n \times n$ matrix:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}$$

where $a_{ii}=1, a_{ij}=1/a_{ji}, a_{ij}\neq 0$.

Based on this pairwise comparison matrix, the weights of the evaluation index system are calculated using the following method:

Step 1: Multiply the values at each row of the pairwise comparison matrix, and then extract the nth root of the product, as shown in Eq. (21):

$$c_i = \sqrt[n]{\prod_{j=1}^{n} a_{ij}} \tag{21}$$

Step 2: Calculate the weight of each index according to Eq. (22).

$$w_i = \frac{c_i}{\sum_{i}^{n} c_i} \tag{22}$$

Step 3: Obtain the weight vector using Eq. (23).

$$\mathbf{W} = \left\{ w_i \middle| i = 1, 2, \ldots n \right\} \tag{23}$$

Because the values in a pairwise comparison matrix are usually given by decision makers and specialists, judgment inconsistency might result from subjective opinions when evaluating the importance of different indices. When the inconsistencies are severe, a reevaluation is required. Inconsistencies can be determined using the eigenvalues in the pairwise comparison matrix, and the specific steps are as follows:

Step 1: Sum the elements of each column in the matrix, as shown in Eq. (24)

$$S_j = \sum_{i=1}^{n} a_{ij} \tag{24}$$

Step 2: Calculate the maximum eigenvalue $\lambda_{\max}$ of the matrix according to Eq. (25).

$$\lambda_{\max} = \sum_{i=1}^{n} w_i S_i \tag{25}$$

Step 3: The ratio of the consistency index C_I to the average random consistency index R_I is called the consistency ratio C_R, which is used to define the consistency of the pairwise comparison matrix, as shown in Eqs. (26) and (27).

$$C_I = \frac{\lambda_{\max} - n}{n-2} \tag{26}$$

$$C_R = \frac{C_I}{R_I} \tag{27}$$

where the values of R_I for the matrices are listed in Table 3.

Generally speaking, when C_R <0.1, the pairwise comparison matrix is considered to have a high consistency; if C_R ≥0.1, the matrix is considered to have poor consistency, which needs adjustments until the consistency requirement is met.

4.2 PROMETHEE-based evaluation process for reconfiguration schemes

The evaluation process for reconfiguration schemes based on the PROMETHEE approach [17–23] is divided into the following five steps:

Step 1: Calculate the value of the preference function of the evaluation index for the RMS reconfiguration schemes. The selection of a preference function is based on the characteristics of the quantitative data obtained for each of the indices of the RMS evaluation index system. Based on the deviation in the index data, the value of the preference function can be calculated according to Eqs. (28) and (29).

$$p_i(a,\ b) = \begin{cases} F_i[d_i(a,\ b)] & \text{when } d_i(a,\ b) > 0 \\ 0 & \text{when } d_i(a,\ b) \leq 0 \end{cases} \tag{28}$$

$$\begin{gathered} d_i(a,\ b) = f_i(a) - f_i(b) \\ \{f_i(a), f_2(a), \ldots, f_n(a) | a \in A\} \end{gathered} \tag{29}$$

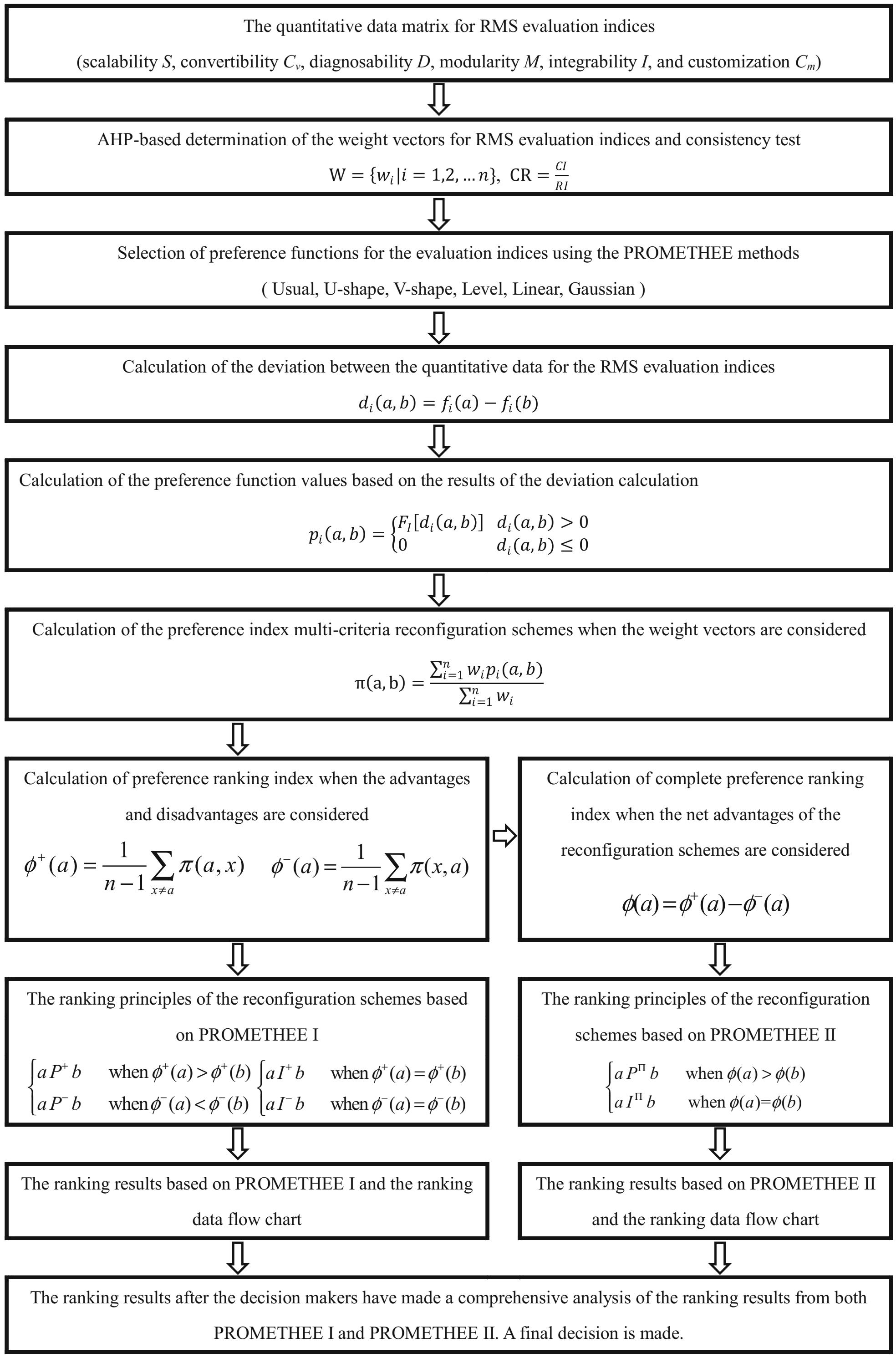

Fig. 1 Flowchart of reconfiguration scheme evaluation based on RMS key characteristics and PROMETHEE

where $f_i(a)$ is the quantitative data of index i for alternative a, and $f_i(b)$ is the quantitative data of index i for alternative b. **A** refers to the set of alternative candidate reconfiguration schemes. $d_i(a,b)$

Table 3 Average consistency index

Order of the matrix (n)	3	4	5	6	7	8	9
The average random consistency index(R_I)	0.58	0.9	1.12	1.24	1.32	1.41	1.45

Table 4 Related parameter data of 10 alternative schemes

Index	Parameter	Scheme 1	2	3	4	5	6	7	8	9	10
Scalability	$\Delta_{\max}$	1100	1100	1300	1300	1000	1500	1400	1700	2000	1600
	$\Delta_{\min}$	100	200	500	300	300	100	300	500	350	200
	N_{Δ}	10	9	2	2	14	7	5	3	11	4
	$\Delta_{\max}$	0.5	0.45	0.38	0.323	0.5	0.52	0.5	0.3	0.5	0.375
	λ_i^C	0.44	0.476	0.42	0.41	0.378	0.39	0.5	0.491	0.3	0.412
	Δ_i	100	100	400	500	50	200	250	500	150	400
	α_i	1.5	2.5	3.1	4.75	2.12	4.22	2.89	6.12	2.56	5.11
Convertibility	C_1	1	0.8	1.25	0.75	0.6	0.636	0.429	0.5	0.571	0.556
	C_2	0.284	0.282	0.189	0.249	0.216	0.294	0.408	0.355	0.267	0.197
	ω_1	3	4	5	3	6	7	6	4	4	5
	ω_2	1	2	2	0	3	2	3	0	4	3
	N_p	1	2	1	3	3	5	6	4	2	1
	N_s	1	1	1	1	4	4	5	4	1	5
	N_t	0.44	0.71	0.66	0.67	0.58	0.378	0.49	0.564	0.625	0.633
	N_f	2	1	1	1	1	1	1	2	1	1
	S_c	0	1	1	2	2	4	0	1	4	1
	N_a	2	2	0	1	2	1	3	2	0	1
	N_d	4	1	6	2	3	3	1	0	1	5
	N_r	0.52	0.413	0.33	0.56	0.61	0.47	0.51	0.511	0.601	0.578
	N_m	0.48	0.587	0.67	0.44	0.39	0.53	0.49	0.489	0.399	0.422
Diagnosability	N_{D}	3	10	4	2	5	6	3	8	1	7
	λ_i^d	5	2	3	3.2	4	2.5	1	2	6	3
	λ_i^s	8	6.667	4	7	6	3.81	3	4.8	8.33	4
	λ_i^T	1	2.5	2	1.75	2	2.9	4	2.12	0.9	1.87
	X_i	0.901	0.923	0.892	0.951	0.805	0.888	0.99	0.796	0.85	0.8896
Modularity	M_1	0.182	0.218	0.158	0.165	0.238	0.172	0.203	0.172	0.175	0.094
	M_2	0.176	0.46	0.77	0.307	0.894	0.16	0.155	0.263	0.148	0.145
	ω_1	0.513	0.475	0.564	0.612	0.39	0.53	0.467	0.493	0.541	0.55
	ω_2	0.487	0.525	0.436	0.388	0.61	0.47	0.533	0.507	0.459	0.45
	G_i	0.91	0.871	0.95	0.99	0.95	0.86	0.81	0.86	0.7	0.94
	G_k	0.88	0.92	0.77	0.92	0.894	0.8	0.93	0.79	0.89	0.87
	N_{ij}	5	4	6	6	4	5	4	5	4	10
	N_{kl}	5	2	1	3	1	5	6	3	6	6
	N_{Δ}	3	5	4	4	6	2	2	3	7	3
	N_k	2	3	2	5	4	4	6	4	5	2
	N_{i}	30	43	22	35	27	60	48	44	31	50
Integrability	α	0.88	0.7	0.77	0.9	0.864	0.892	0.94	0.92	0.86	0.867
	β	0.912	0.8	0.82	0.84	0.87	0.798	0.85	0.7	0.86	0.9
	ω_1	0.513	0.55	0.57	0.65	0.611	0.574	0.56	0.54	0.52	0.58
	ω_2	0.487	0.45	0.43	0.35	0.389	0.426	0.44	0.46	0.48	0.42
Customization	λ_T	0.9	0.7	0.4	0.5	0.9	0.95	0.94	0.95	0.7	0.6
	P	1	1	4	3	5	2	1	1	2	1
	Y	0.85	0.91	0.951	0.96	0.67	0.85	0.901	0.79	0.843	0.73

denotes the deviation between alternatives a and b associated with index i. $p_i(a,b)$ denotes the preference degree of alternative a over b, in terms of index i, i.e., preference function value $0 \leq p_i(a,b) \leq 1$. F_i denotes the preference function selected by the decision maker based on the characteristics of index i.

Table 5 Evaluation index of 10 alternative schemes

Index	Scheme									
	1	2	3	4	5	6	7	8	9	10
S	0.967	0.94	0.753	0.685	0.971	0.878	0.835	0.624	0.965	0.774
C_v	0.656	0.496	0.539	0.529	0.45	0.455	0.419	0.429	0.45	0.404
D	108.1	307.7	85.67	74.56	193.1	147.1	35.64	129.7	38.25	139.7
M	0.179	0.345	0.425	0.22	0.638	0.166	0.177	0.218	0.163	0.117
I	0.896	0.745	0.792	0.879	0.866	0.852	0.9	0.819	0.86	0.881
C_m	0.7	0.64	0.38	0.48	0.6	0.81	0.85	0.75	0.59	0.4

Step 2: Calculate the preference function for the evaluation of the RMS reconfiguration schemes. The evaluation index system for the RMS reconfiguration schemes includes six evaluation indices, and the preference function value for each of these six evaluation indices is obtained after a pairwise comparison of the alternatives in set A. The weighted average of the preference function values between the alternatives is obtained using the weight assignment method described in Sect. 3.1—this is the preference index for the evaluation of the RMS reconfiguration schemes, which is defined as $\pi(a, b)$ (Eq. (30)).

$$\pi(a,b) = \sum_{i=1}^{n} w_i p_i(a,b) \tag{30}$$

where $0 \leq \pi(a, b) \leq 1$. A $\pi(a, b)$ value closer to 1 would suggest that the decision maker prefers alternative a rather than alternative b.

Step 3: Calculate the ranking index for the evaluation of the RMS reconfiguration schemes. The preference index $\pi(a, x)$ only gives the preference relationship between alternative a and other alternatives of set **A** after pairwise comparisons. It is necessary to further determine the evaluation value of alternative a among all the alternatives, i.e., the sum of the preference indices of alternative a and all the remaining alternatives in the set, which is used as the evaluation value to indicate the evaluation ranking, as shown in Eqs. (31) and (32).

$$\phi^{+}(a) = \frac{1}{n-1} \sum_{x \neq a} \pi(a,x) \tag{31}$$

$$\phi^{-}(a) = \frac{1}{n-1} \sum_{x \neq a} \pi(x,a) \tag{32}$$

where $\Phi^{+}(a)$ means the preference degree of the decision maker for alternative a over other alternatives, $\Phi^{+}(a) \geq 0$, i.e., a higher $\Phi^{+}(a)$ value indicates a higher tendency for the decision maker to choose alternative a, whereas a low value indicates that the probability of alternative a being selected is very low, even zero. $\Phi^{-}(a)$ means the degree of disfavor of the decision maker for alternative a over other alternatives, i.e., the tendency that the decision maker would choose other alternatives, $\Phi^{-}(a) \geq 0$, i.e., a $\Phi^{-}(a)$ value closer to zero indicates a higher tendency for the decision maker to choose alternative a.

Step 4: Use the PROMETHEE I method to rank the ranking indices for evaluating the RMS reconfiguration schemes. These evaluation-ranking indices give the evaluation values of the alternatives, including the strengths and weaknesses of the reconfiguration schemes. The ranking of the alternatives in set **A** is conducted according to the ranking principles given in Eqs. (33) and (34).

$$\begin{cases} aP^{+}b & \text{when}\phi^{+}(a) > \phi^{+}(b) \\ aP^{-}b & \text{when}\phi^{-}(a) < \phi^{-}(b) \end{cases} \tag{33}$$

$$\begin{cases} aI^{+}b & \text{when}\phi^{+}(a) = \phi^{+}(b) \\ aI^{-}b & \text{when}\phi^{-}(a) = \phi^{-}(b) \end{cases} \tag{34}$$

where P^{+} and P^{-} suggest that alternative a has greater advantages over alternative b, i.e., the decision maker prefers alternative a. I^{+} and I^{-} suggest that there is no significant advantages or disadvantages between alternatives a and b, i.e., the decision maker does not have a preference between these two alternatives.

Table 6 Data rankings

Index										
S	0.624	0.685	0.753	0.774	0.835	0.878	0.94	0.965	0.967	0.971
C_v	0.404	0.419	0.429	0.45	0.45	0.455	0.496	0.529	0.539	0.656
D	35.64	38.25	74.56	85.67	108.1	129.7	139.7	147.1	193.1	307.7
M	0.117	0.163	0.166	0.177	0.179	0.218	0.22	0.345	0.425	0.638
I	0.745	0.792	0.819	0.852	0.86	0.866	0.879	0.881	0.896	0.9
C_m	0.38	0.4	0.48	0.59	0.6	0.64	0.7	0.75	0.81	0.85

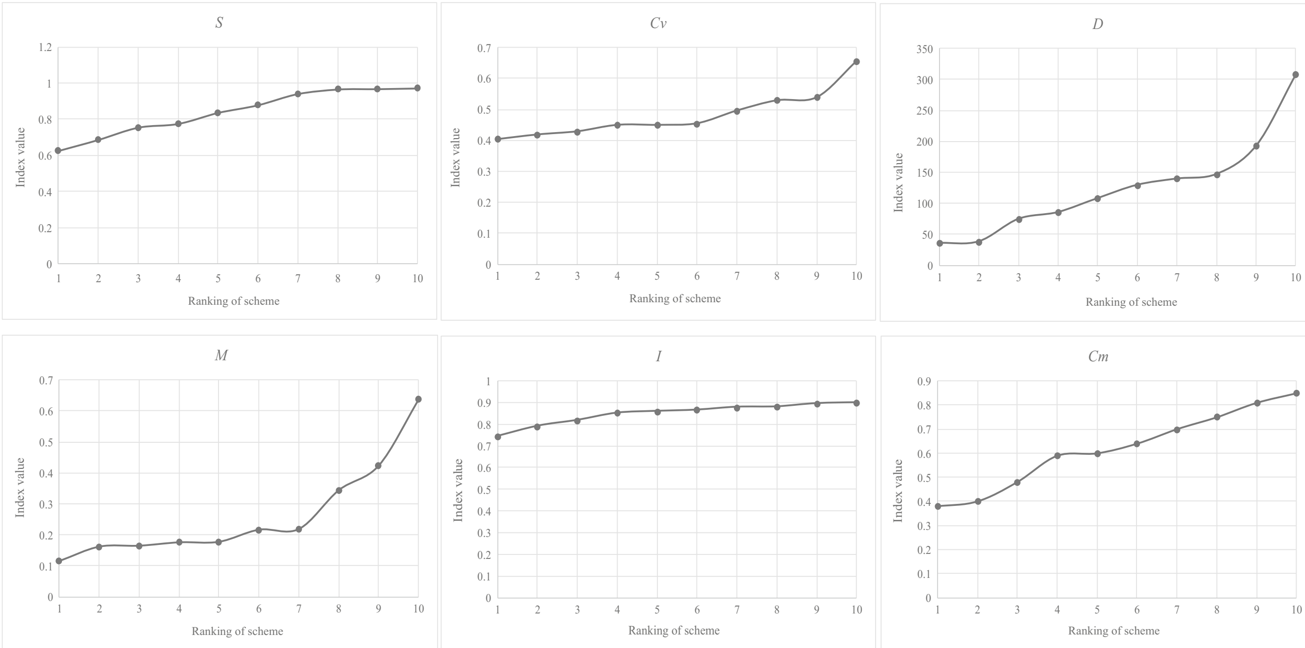

Fig. 2 Chart of evaluation index quantitative data

There are three ranking relations in the ranking of the alternative reconfiguration schemes: alternative a is better than alternative b, there is no difference between alternatives a and b, and alternatives a and b cannot be compared with each other. The ranking principles for evaluating the alternatives are classified based on these three relations, as shown in Eq. (35).

$$\begin{cases} aP^I b & \text{when} \begin{cases} a\,P^+\,b\&a\,P^-\,b \\ a\,P^+\,b\&a\,I^-\,b \\ a\,I^+\,b\&a\,P^-\,b \end{cases} \\ aI^I b & \text{when } a\,I^+\,b\&a\,I^-\,b \\ aRb & \text{others} \end{cases} \tag{35}$$

where P^{I} suggests that the decision maker prefers alternative a, i.e., when $\Phi^+(a) > \Phi^+(b)$ and $\Phi^-(a) < \Phi^-(b)$, or $\Phi^+(a) > \Phi^+(b)$ and $\Phi^-(a) = \Phi^-(b)$, or $\Phi^+(a) = \Phi^+(b)$ and $\Phi^-(a) < \Phi^-(b)$, alternative a is more advantageous than b. I^{I} suggests that there is no relationship between these two alternatives, i.e., when $\Phi^+(a) = \Phi^+(b)$ and $\Phi^-(a) = \Phi^-(b)$, their selection probabilities are the same. R suggests that alternatives a and b cannot be compared with each other. This occurs when one alternative simultaneously has more advantages and disadvantages than the others, which makes it impossible to make comparisons, i.e., $\Phi^+(a) > \Phi^+(b)$ and $\Phi^-(a) > \Phi^-(b)$.

Step 5: Calculate the complete ranking index for the evaluation of the RMS reconfiguration schemes, i.e., the net advantage of an alternative. The categorization results derived from Eq. (35) include a category in which the alternative has both strong advantages and disadvantages, and as a result neither a comparison nor ranking can be conducted. Therefore, a complete ranking index is proposed for the evaluation of RMS reconfiguration schemes to make up for the deficiency of the (partial) ranking index, as shown in Eq. (36).

$$\phi(a) = \phi^+(a) - \phi^-(a) \tag{36}$$

Step 6: Use the PROMETHEE II method to obtain the ranking of the complete ranking indices for the evaluation of the RMS reconfiguration schemes. The ranking principles for the complete ranking index of the RMS reconfiguration schemes is shown in Eq. (37), according to which there are two relations

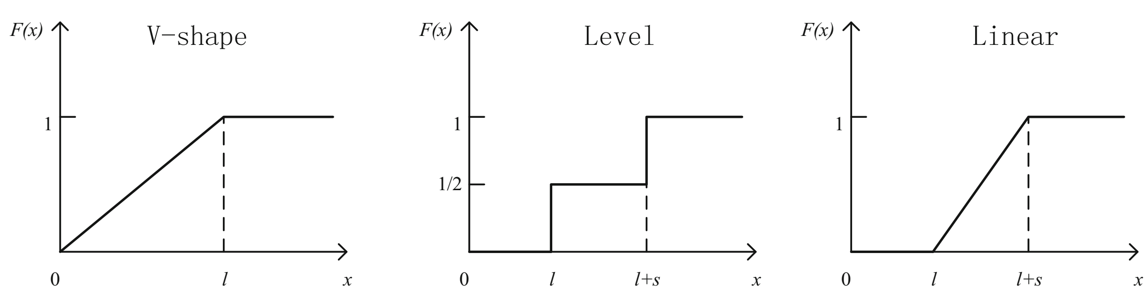

Fig. 3 Graphs of V-shape, level, and linear preference functions [14]

Table 7 Preference functions selected and related parameters determined

Index	Preference function	Deviation parameters	
		l	$l+s$
S	Linear	0.1	0.22
C_v	Level	0.15	0.3
D	Level	120	280
M	Linear	0.05	0.1
I	V-shape	0.01	
C_m	Level	0.3	0.45

between alternatives: alternative a is better than alternative b, or there is no difference between alternatives a and b.

$$\begin{cases} aP^{\Pi}b & \text{when}\phi(a) > \phi(b) \\ aI^{\Pi}b & \text{when}\phi(a) = \phi(b) \end{cases} \tag{37}$$

where P^{Π} suggests that the decision maker prefers alternative a. I^{Π} suggests that the decision maker does not have a preference between these two alternatives.

Step 7: Analyze the ranking results for the evaluation of the RMS reconfiguration schemes, and draw the ranking data flow diagram. The mapping of the ranking data flow diagram is based on the ranking results, in order to reflect the advantage/disadvantage relations between alternatives.

The PROMETHEE I method evaluates the alternatives from two perspectives: the advantages and disadvantages. The PROMETHEE II method gives a comprehensive evaluation by calculating the difference between the advantages and disadvantages of the reconfiguration schemes, which allows it to rank alternatives that PROMETHEE I cannot rank. PROMETHEE II takes into account the new advantage of an alternative while neglecting specific advantage/disadvantage values of the alternative, which might result in the occurrence of "false-advantageous" alternatives. In order to obtain reasonable ranking results during the evaluation of alternative schemes, it is necessary to comprehensively assess the methods of PROMETHEE I and PROMETHEE II. (1) If the decision maker is more concerned about the advantages of the alternatives, the PROMETHEE I method can be used to rank them, and the alternative with the most advantages can be selected. (2) If the decision maker is more concerned about the disadvantages of the alternatives, i.e., fewer disadvantages are desired, the PROMETHEE I method can be used to rank them, and the alternative with the least disadvantages can be selected. (3) If the decision maker takes into account both the advantages and disadvantages of the alternatives, the PROMETHEE II method can be used to give the complete ranking of the alternatives, and the alternative with the largest complete ranking index can be selected. The process used for this algorithm is presented in Fig. 1.

Table 8 Comparison matrix of evaluation index

	S	C_v	D	M	I	C_m
S	1	2/3	3/5	6/7	3/5	5/3
C_v	3/2	1	4/5	5/4	3/1	4/3
D	5/3	5/4	1	3/5	3/1	5/3
M	7/6	4/5	5/3	1	5/4	5/4
I	5/3	1/3	1/3	4/5	1	4/5
C_m	3/5	3/4	1/2	4/5	5/4	1

Table 9 Ranking index calculation results of 10 schemes

Scheme	Φ^{+}	Φ^{-}	Φ
Scheme 1	0.1928	0.0807	0.1121
Scheme 2	0.2756	0.1504	0.1251
Scheme 3	0.1720	0.1594	0.0126
Scheme 4	0.0951	0.1148	-0.0197
Scheme 5	0.2687	0.0589	0.2098
Scheme 6	0.0545	0.1583	-0.1038
Scheme 7	0.1277	0.1143	0.0134
Scheme 8	0.0604	0.1697	-0.1093
Scheme 9	0.0439	0.1726	-0.1286
Scheme 10	0.0716	0.1832	-0.1116

1 Experimental verification

A research institute-affiliated workshop that possesses both research and production capability is used as an example to verify the method proposed in this paper. Product pre-research requires both product diversity and customization. In addition, because of the special need for certain types of parts, the workshop must be capable of batch production. In order to satisfy the requirements stated above, adjustments of the system and equipment are required for different production tasks. However, a certain risk exists during each adjustment, which requires the support of an effective evaluation method (Table 3).

1.1 Experimental data entry and index calculation

In this paper, the acquisition and analysis of parameter data relevant to the evaluation indices are based on the historical data obtained from the workshop. Each column in Table 4 represents an evaluation scheme. Each scheme involves six evaluation indices, and each index corresponds to a series of parameters (e.g., the maximum production capacity ($\Delta_{\max}$) of scalability, minimum production capacity ($\Delta_{\min}$), and conversion capacity within a part family of convertibility C_1). Each row in the table represents the specific values of the parameter

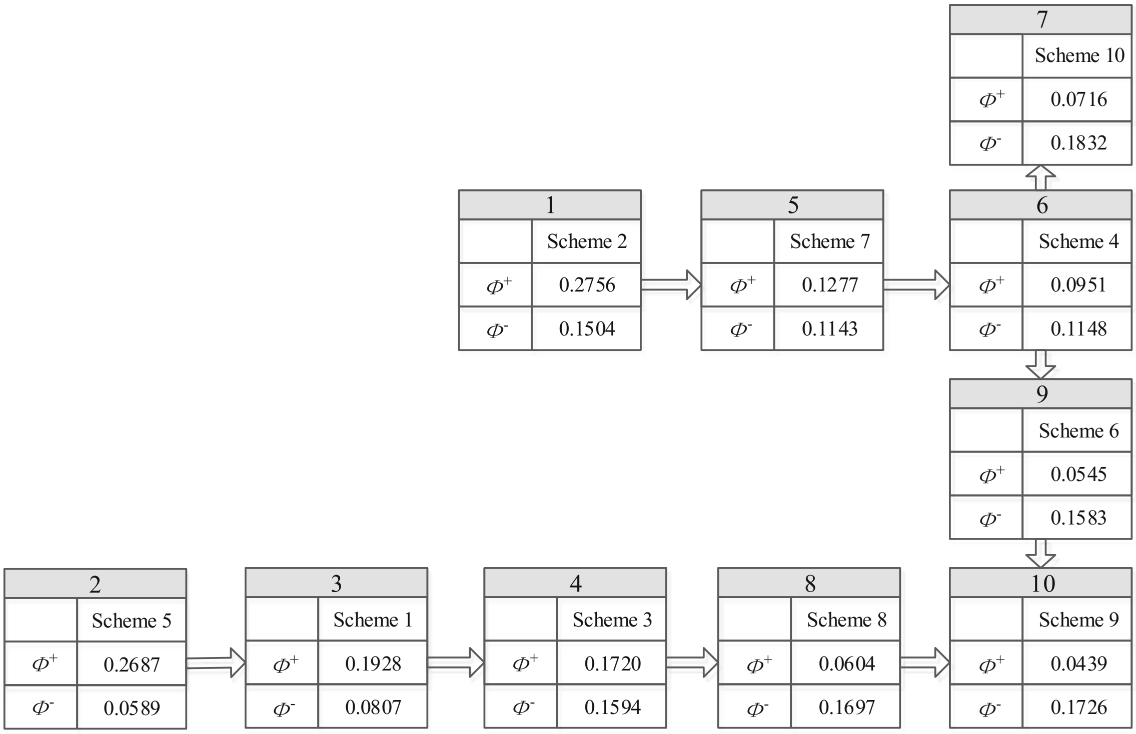

Fig. 4 PROMETHEE I partial rankings

for different schemes. According to the index quantitative models for RMS evaluation developed in Sect. 3, the index data for the 10 candidate schemes are calculated using the data in Table 4. The results are listed in Table 5, where each column represents an evaluation scheme, and each scheme contains the data calculated for the six evaluation indices. In addition, each row in Table 4 represents the specific values of an evaluation index for different schemes.

1.2 Evaluation process for reconfiguration schemes

Table 6 lists the ranking results for the data obtained (Table 5) for the six evaluation indices. Except for the scalability, larger values for the evaluation indices indicate better system performance. Therefore, an ascending ranking is used for the index data (excluding the scalability data) and a descending ranking is used for the scalability data. Figure 2 shows the data trends based on the ranking results of Table 6.

The preference function for each RMS evaluation index is selected based on the trend graphs of the evaluation indices (Fig. 2) and the definitions and explanations of the preference functions (Fig. 3) given in a previous study [20]. The scalability (S) and modularity (M) data are characteristic of the lowest level in some data, while the rest of the data exhibit a linear trend. For example, the values on the left side of the M data are almost equal to each other, i.e., the lowest level, after which the data exhibit a linear trend. The same characteristic is found in the S data. Therefore, linear preference functions can describe the evaluation indices S and M more accurately. The data for the convertibility (Cv), diagnosability (D), and customization (Cm) exhibit significant hierarchical properties, and therefore, level preference functions are used to describe these indices. The integrability (I) data are characterized by a linear change, where significant preference intervals are found, and therefore, the V-shape preference function is used to describe this index. Table 7 lists the selections of the preference functions for the indices and the relevant parameters.

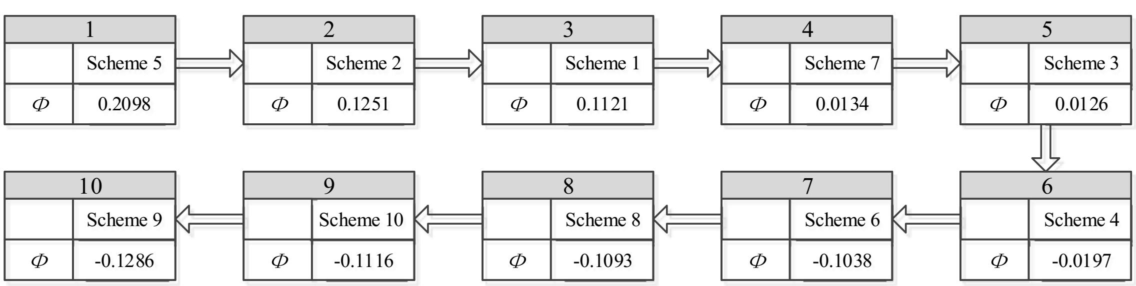

Fig. 5 PROMETHEE II complete rankings

Table 10 Relationship between index and parameter

Index		Scheme												
	Parameter	1	2	3	4	5	6	7	8	9	10	11	12	13
	$\Delta_{\max}$	1100	1200	1300	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
	$\Delta_{\min}$	100	100	100	200	300	100	100	100	100	100	100	100	100
	λ_i^T	0.5	0.5	0.5	0.5	0.5	0.7	0.9	0.5	0.5	0.5	0.5	0.5	0.5
	λ_i^C	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.6	0.8	0.4	0.4	0.4	0.4
	Δ_i	100	100	100	100	100	100	100	100	100	150	200	100	100
	α_i	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	4	6
S		0.97	0.973	0.975	0.967	0.963	0.958	0.946	0.955	0.94	0.955	0.94	0.92	0.88

Based on professional experience, the importance of each evaluation index is analyzed and their weights are determined using the weight calculation method for an evaluation index described in Sect. 4.1.

The importance values listed in Table 8 are used as the input data for calculating the weights of the six evaluation indices (scalability, convertibility, diagnosability, modularity, integrability, and customization) according to Eq. (21), from which the weight vectors are obtained: $\mathbf{C} = [0.807; 1.431; 1.443; 1.194; 0.653; 0.742]$. Then, the weights are normalized according to Eqs. (22) and (23), from which normalized weight vectors are obtained: $\mathbf{W} = [0.129; 0.228; 0.23; 0.19; 0.104; 0.119]$. The maximum eigenvalue is calculated ($\lambda_{\max} = 6.177$) according to Eqs. (24) and (25), and the consistency index is calculated ($C_I = 0.044$) according to Eq. (26). Combined with Table 2, the consistency ratio is calculated using Eq. (27), and the result is $C_R = 0.036 < 0.1$, indicating that the comparison matrix in Table 8 has passed the consistency test. Therefore, the weight vectors assigned for the evaluation indices of the RMS reconfiguration schemes are $\mathbf{W} = [0.129; 0.228; 0.23; 0.19; 0.104; 0.119]$.

Based on the weight distribution results described above, the evaluation of the schemes is carried out using the PROMETHEE approach (including PROMETHEE I and PROMETHEE II). The deviation in the value of each evaluation index between each scheme and the other nine schemes is calculated using Eqs. (30) and (31). The P_i value and preference indices ($\pi(1, x)$ and $\pi(x, 1)$) are calculated by substituting this deviation into the preference function of each index. The PROMETHEE I partial ranking indices (Φ^+, Φ^-) of each scheme are calculated according to Eqs. (33) and (34), and the PROMETHEE II complete ranking index (Φ) of each scheme is calculated according to Eq. (38), which is the difference between Φ^+ and Φ^-. The PROMETHEE I partial ranking indices and PROMETHEE II complete ranking indices for all 10 schemes are organized and listed in Table 9.

Based on the data listed in Table 9, the schemes are ranked according to the ranking principles of PROMETHEE I and PROMETHEE II, and the ranking results are shown in Figs. 4 and 5. As shown in Fig. 4, when only the scheme advantages are considered, scheme 2 would be the best and scheme 9 would be the worst. However, the relations between scheme 2 and scheme 5, scheme 3 and scheme 7, scheme 6 and scheme 10, and scheme 9 and scheme 10 all belong to the third relation ($R(\Phi^+(a) > \Phi^+(b)$ and $\Phi^-(a) > \Phi^-(b))$ described in Eq. (37), i.e., the advantages and disadvantages are both significant for these schemes. Thus, the ranking of these schemes cannot be performed. Therefore, the ranking needs to be further determined using the data flow chart of the PROMETHEE II method. Figure 5 shows the ranking results of the PROMETHEE II complete ranking method. As shown in the figure, scheme 5 becomes the best scheme while

Table 11 Evaluation index of 13 alternative schemes

	Scheme												
Index	1	2	3	4	5	6	7	8	9	10	11	12	13
S	0.970	0.973	0.975	0.967	0.963	0.958	0.946	0.955	0.94	0.955	0.94	0.92	0.88
C_v	1	1	1	1	1	1	1	1	1	1	1	1	1
D	1	1	1	1	1	1	1	1	1	1	1	1	1
M	1	1	1	1	1	1	1	1	1	1	1	1	1
I	1	1	1	1	1	1	1	1	1	1	1	1	1
C_m	1	1	1	1	1	1	1	1	1	1	1	1	1
w	1	1	1	1	1	1	1	1	1	1	1	1	1

Table 12 Ranking index calculation results 13 alternative schemes

Scheme	Φ^+	Φ^-	Φ
Scheme 1	0.2	0	0.2
Scheme 2	0.2267	0	0.2267
Scheme 3	0.2467	0	0.2467
Scheme 4	0.17	0	0.17
Scheme 5	0.1433	0	0.1433
Scheme 6	0.1267	0	0.1267
Scheme 7	0.0867	0.02	0.0667
Scheme 8	0.1167	0	0.1167
Scheme 9	0.0833	0.0833	0
Scheme 10	0.1167	0	0.1167
Scheme 11	0.0833	0.0833	0
Scheme 12	0.05	0.4967	-0.4467
Scheme 13	0	0.9667	-0.9667

scheme 9 remains the worst. The figure also shows that scheme 5 is better than scheme 2, and scheme 1 is better than scheme 7, while schemes 3, 4, 6, 8, 10, and 9 are ranked as stated. The comprehensive ranking results for the RMS reconfiguration schemes in descending order based on PROMETHEE II are as follows: scheme 5, scheme 2, scheme 1, scheme 7, scheme 3, scheme 4, scheme 6, scheme 8, scheme 10, and scheme 9. Therefore, the PROMETHEE II complete ranking method is able to solve the ranking problem that occurs during the ranking with the PROMETHEE I method, providing clear ranking results for schemes with both advantages and disadvantages.

The PROMETHEE I method enables a partial evaluation of the reconfiguration schemes, which allows decision makers to screen the schemes based on the advantages or disadvantages of alternative schemes before making the final decision. Decision makers who are more concerned about the advantages of a scheme can select scheme 2, because the advantage index value of scheme 2 is 0.2756—the largest among the schemes. Decision makers who are more concerned about the disadvantages of a scheme can select scheme 5, because the disadvantage index value of scheme 5 is 0.0589—the lowest among the schemes. PROMETHEE II offers a complete evaluation of the reconfiguration schemes, which takes into account both the advantages and disadvantages of the schemes, enabling the selection of a "satisfactory solution." This means that when the best scheme with the most advantages and fewest disadvantages is not identifiable, decision makers can consider both the advantages and disadvantages of the schemes and select the one with more advantages and fewer disadvantages. For example, scheme 2 shown in Fig. 5 has the maximum advantage index value, but its disadvantage index value is also large. Therefore, it cannot be considered to be a satisfactory solution. However, while the advantage index value of scheme 5 is not the largest (it ranks 2nd), its disadvantage index value is the smallest. Thus, it can be used as a "satisfactory solution" after a comprehensive consideration.

1.3 Evaluation results analysis and visual verification

The key step of the proposed method is the construction of quantitative models of RMS key characteristics as evaluation index system, which is the initial point of the whole reconfiguration scheme evaluation process. Each evaluation index

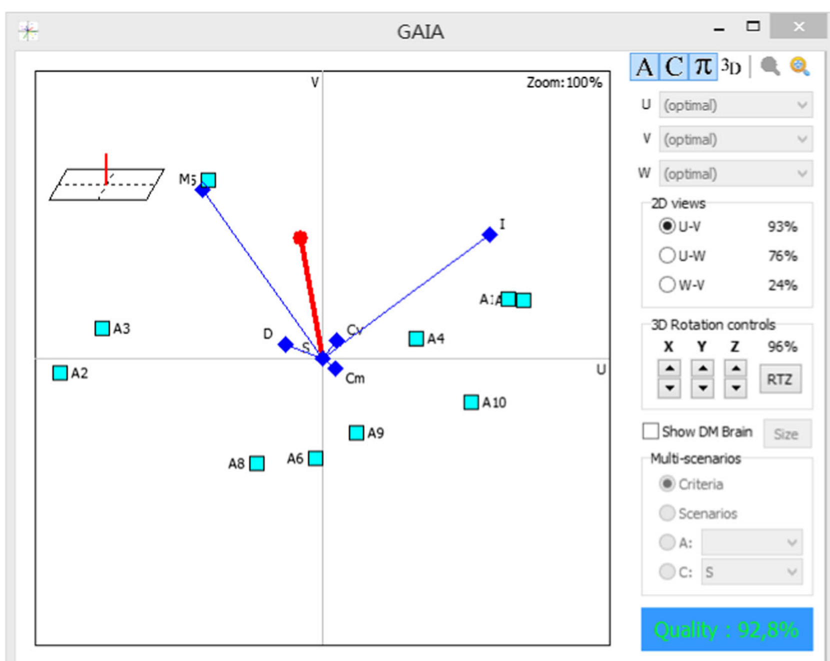

Fig. 6 GAIA plane analysis

consists of selecting parameters and the parameter that determines the index's value, which determines the prioritization of schemes. For example, scalability consists of seven parameters, such as Δ_{max}, Δ_{min}, N_{Δ}, λ_i^T, and so on. In addition, these parameters are mutually independent, except for N_{Δ} whose value relies on the value of Δ_{max}, Δ_{min}, and Δ_i. So the value of six independent parameters are analyzed by controlling the variable method, as shown in Table 10, where each column represents a scheme. Scheme 1 was selected as the basic scheme, and each other scheme compares with it. In Table 10, the value of S is in proportion to Δ_{max} and inversely proportional to Δ_{min}, λ_i^T, λ_i^C, Δ_i, and α_i. Consequently, improving the Δ_{max} value and simultaneously reducing other values in design processing can make the scalability of the scheme better. Based on the data of Table 10, an evaluation case only considering the variation of scalability was constructed, as shown in Table 11. According to data characteristics of the S index, the linear type preference function was chosen ($l = 0.025$, $l + s = 0.05$). PROMETHEE I and PROMETHEE II algorithms were used to evaluate the 13 schemes in Table 11, and evaluation results were shown in Table 12. Consequently, scheme 3 is the optimal scheme, which matches with the fact that the scalability value of scheme 3 is the maximum in Table 11. In other words, the scalability has a positive impact on scheme ranking. Moreover, other evaluation indices can draw the same conclusion.

Figure 6 displays the visual decision output using the GAIA plane. In this figure, the squares represent the alternative schemes, diamonds represent the evaluation indices, and the line connecting the evaluation index and the origin point denotes the degree of relevance. The line connecting the dot and the origin point constitutes the decision axis, representing the evaluation results, with a shorter distance between a scheme and the dot implying a superior scheme. In the figure, scheme 5 has the shortest distance to the dot compared to the other schemes, showing that scheme 5 is the best scheme, which is consistent with the result of the complete ranking, demonstrating the accuracy of the evaluation method proposed in this paper. In addition, the quality index at the bottom right corner of Fig. 6 is 92.8 %, indicating that there is only a 7.2 % data loss during the evaluation, which is considered a low data loss. Because a certain number of the simplifications made during data processing inevitably result in data loss, a lower data loss would suggest that the evaluation results are closer to the actual situation. Therefore, the calculation methods proposed in this paper are both valid and practical.

2 Conclusion and outlook

During RMS reconfiguration, the designers of new configurations may provide a variety of feasible reconfiguration schemes (alternatives) based on different emphases when considering numerous factors such as the reconfiguration cost, responsiveness, and reconfiguration difficulty. Therefore, the evaluation and comparison of different configuration alternatives to identify the most suitable configuration have become critical steps for the successful completion of a system reconfiguration.

The evaluation and comparison of alternative reconfiguration schemes is a multi-criteria decision-making problem. An evaluation method for RMS reconfiguration schemes that is based on the preference ranking of key RMS characteristics was proposed in this paper. First, quantitative models were developed for the evaluation indices of the reconfiguration schemes based on the RMS key characteristics. Next, an integrated AHP method and a two-phase PROMETHEE method were used to achieve a comprehensive evaluation of the alternative reconfiguration schemes, using the AHP method to make up for the inability of the PROMETHEE method to give index weights. The RMS key characteristics essentially reflect RMS properties. Previous research defined and explained these key characteristics, but quantitative studies on the RMS key characteristics are scarce. Thus, the significance of these key characteristics has not been demonstrated in practical applications. Therefore, quantitative models were developed in this paper for the RMS key characteristics, which were based on the analysis of these characteristics at multiple levels such as machine tools and units. This study represented a breakthrough from previous research on RMS key characteristics, which has been limited to pure qualitative descriptions, and increases the possibility of the practical application of RMS key characteristics. The PROMETHEE evaluation methods were used to analyze the advantages/disadvantages of alternatives in two ways—partially and completely, which solved the ranking problem of alternatives with significant advantages and disadvantages. As a result, "false-advantageous" alternatives could be excluded, and the most suitable scheme for real-world production could be selected. As shown in the experimental verification results, the PROMETHEE I method was able to provide advantage/disadvantage values for each alternative scheme, which would allow decision makers to make a decision based on different emphases. The experiment showed that using the key characteristics as the evaluation indices could essentially reflect the RMS properties, ensuring the validity of the evaluation. Moreover, the establishment of quantitative models for the evaluation indices realized the conversion from a qualitative subjective evaluation to a quantitative objective evaluation. A visual verification (GAIA) of the evaluation results showed that they were in accordance with those derived from the calculation methods proposed in this paper, proving the accuracy and validity of the calculation methods.

In this paper, an evaluation method was proposed for RMS reconfiguration schemes. This is an evaluation index system that was developed based on RMS key characteristics and can be used for an effective configuration evaluation during the design stage. However, production factors such as production cost and batch size are not included during the evaluation process. Therefore, in future research, it is necessary to combine the actual production conditions and take into account factors such as the production cost and batch size, in order to obtain evaluation results that are closer to reality.

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